KSCE Journal of Civil Engineering (2019) 23(7):3174-3179

DOI 10.1007/s12205-019-0833-4

TECHNICAL NOTE

Transportation Engineering

pISSN 1226-7988, eISSN 1976-3808
www.springer.com/12205

Mitigating Recurrent Congestion via Particle Swarm Optimization Variable Speed Limit Controllers

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Received June 26, 2017/Revised May 31, 2018/Accepted March 28, 2019/Published Online May 10, 2019

Abstract

Variable speed limit (VSL) has proven to be an efficient motorway control measure to mitigate traffic congestion at motorway bottlenecks. VSL can reduce the effect of shockwave on traffic conditions through smoothing the transition between the congested downstream and upstream traffic flows. In this paper, a particle swarm optimization (PSO) based VSL method is proposed to minimize the probability of flow breakdown at bottleneck sections and ensure a maximum utilization of the current motorway infrastructure. The results show that the motorway system equipped with PSO based VSL outperformed the one with rule based VSL.

Keywords: *variable speed limit, particle swarm optimization, motorway traffic control, simulation, congestion reduction*

1. Introduction

Variable speed limit (VSL) has proven to be an efficient motorway control tool to mitigate traffic congestion at motorway bottlenecks. VSL can reduce the effect of shockwave on traffic conditions through smoothing the transition between the congested downstream and upstream traffic flows. Dynamically changed and properly displayed speed limit along a controlled segment mitigates stop-and-go traffic speed variance, which results in a better utilization of the available motorway capacity during peak hours.

There are two board types of VSL methods, namely, proactive methods and reactive methods. Reactive methods can be further classified as occupancy-based (Elefteriadou *et al*., 2013), flow-based (Habtemichael and Picado-Santos, 2013), speed-based (Lee *et al*., 2004), and multi-parameters based (Allaby *et al.*, 2007; Kianfar *et al*., 2013; Papageorgiou *et al*., 2008; Li and Ranjitkar, 2015) algorithms. The most prominent example of proactive studies was conducted by Hegyi *et al.* (2005). They proposed a model predictive control (MPC) method to decrease total time spent. The MPC method has proven its effectiveness in subsequent studies (Khondaker and Kattan, 2015; Hadiuzzaman *et al.*, 2013). Nevertheless, proactive approaches are rarely applied in the field because of their complexity.

In previous attempts, several VSL and ramp metering algorithms have been evaluated for Auckland Motorway (Li *et al.*, 2015, 2017), but without the development presented in this work. In this study, a PSO (particle swarm optimization) based VSL method is proposed to minimize flow breakdown probability and ensure a maximum utilization of the current motorway infrastructure. PSO (Eberhart and Kennedy, 1995) is suitable for motorway control systems since: 1) Its search technique uses objective function values instead of gradient information; 2) it is applicable for complex motorway systems as no strong assumption is needed.

2. Methodology

In order to improve traffic mobility at motorway bottlenecks via mitigating traffic congestion, this study started with developing a flow breakdown probability model under different occupancy levels. Then an objective function was formulated for simultaneously minimizing flow breakdown probability and maximizing throughput at bottleneck sections. Finally, PSO method was adapted to minimize the formulated objective function.

Figure 1 shows a flowchart of the PSO based VSL control logic. At each control interval, VSL obtains volume and occupancy data from detectors. Using collected traffic data (input), the formulated objective function (Eq. (5)) is optimized by PSO to obtain desired upstream volume (output). Then, recommended speed limit values in the next interval are calculated via Eq. (6) based on desired upstream volume. Finally, VSL controller sends optimal speed limit values to VMS (variable message signs).

2.1 Flow Breakdown Probability Calculation

Three-month data was collected from State Highway 1 in

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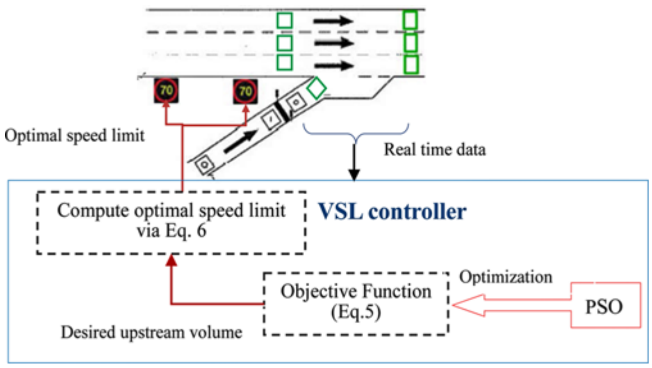

Fig.1. Flowchart of the Proposed VSL Control Logic

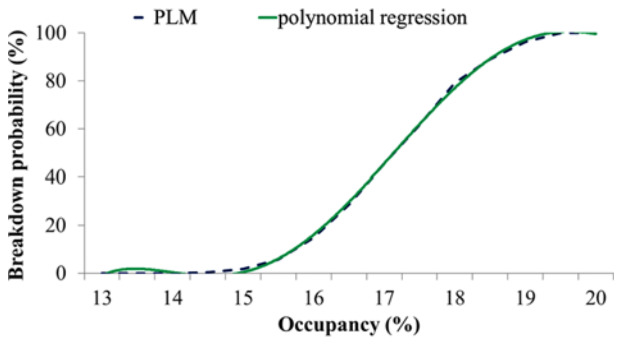

Fig. 2. Occupancy Distribution Just before Flow Breakdown

Auckland. Motorway capacity is defined as the traffic flow above which proper operation fails and below which the performance of the motorway is acceptable (Brilon *et al.*, 2005). The transition between non-acceptable traffic conditions and proper operation can be defined as "flow breakdown". For a given occupancy value O, its flow breakdown probability can be computed by dividing the number of breakdowns that occur at O by the total number of breakdowns. The product limit method (PLM) was adopted to compute the flow breakdown probability $P(O)$ for the occupancy O, which is presented in Fig. 2. Note that detector D1 (see Fig. 4) installed at the critical bottleneck of the selected motorway. Recurrent flow breakdowns were observed in the vicinity of D1, while other detectors recorded few breakdowns. Thus, only occupancy data collected from D1 was used to calculate flow breakdown probability.

2.2 Objective Function Formulation

The total number N of vehicles at time interval $t + 1$ can be computed as:

$$N(t+1) = N(t) + T(q_u(t) + r(t) - q(t)) \tag{1}$$

Where,

t = discrete time step, $t = 1, 2, \ldots$

q_u = the upstream volume (veh/h) at t

q = the downstream volume (veh/h) at t

r = the on-ramp volume (veh/h) at t

T = time interval (h)

Define traffic density as $\rho(t) = N(t)/\Delta x$, where Δx is length of the segment. A basic relationship between volume and density ρ (veh/km) for a motorway section is given as:

$$\rho(t+1) = \rho(t) + T(q_u(t) + r(t) - q(t))/\Delta x \tag{2}$$

The traffic occupancy is approximated by:

$$\tilde{\rho}(t) = O(t) \times 1{,}000/l \tag{3}$$

Where,

$O(t)$ = the occupancy at t

l = the effective vehicle length (m)

Note that 1,000 in Eqs. (3) and (4) means 1,000 meters. Thus, the traffic occupancy of a bottleneck segment b can be computed via:

$$O_b(t+1) = O_b(t) + T(q_c(t) + r_b(t) - q_b(t))l/(1000\Delta x_b) \tag{4}$$

where $q_c(t)$ is the inflow of the bottleneck segment b as well as the outflow of corresponding upstream VSL controlled segment c, which is influenced by the posted speed limit v.

Then, the objective function was formulated. The proposed objective function consists of two components: 1) The flow breakdown probability model $P(O_b(t+1))$ presented in the previous section to minimize the probability of flow breakdown, and 2) a critical occupancy index $O_r/O_b(t+1)$, which can be calculated via Eq. (4), to ensure a maximum utilization of the motorway infrastructure. The objective function aims at locating the optimal upstream volume that minimizes the flow breakdown probability and maximizes the throughput at bottleneck sections:

$$J = P(O_b(t+1) + O_r/O_b(t+1)) \tag{5}$$

where O_r is the critical occupancy. O_r = 17% was selected in this study, which has around 50% probability resulting in flow breakdown.

Since the occupancy $O_b(t)$, on-ramp flow $r_b(t)$, and mainline outflow $q_b(t)$ are obtained from detectors. The optimization problem can be defined as: Finding the inflow $q_c(k) > 0$ that minimizes the objective function described in Eq. (5). The recommended speed limit $v(k)$ at time interval t is calculated by:

$$v(t) = q_{co}(t)/O_c(t+1) \tag{6}$$

Where,

$q_{co}(t)$ = the optimized volume at t

$O_b(t+1)$ = the occupancy of upstream VSL controlled segment c at $t+1$, which can be calculated via Eq. (4)

2.3 PSO Optimization

In PSO process, the individuals are called particles. Each particle represents a candidate solution. At every iteration, each particle "flies" in the search space. Their movements are effected by their local best positions and global best positions attained so far (Kennedy, 1997). Let S denote the population size. n is the problem dimension. The velocity and position of the k'th particle are $x_k = (x_{k1}, x_{k2}, \ldots, x_{kn})$ and $v_i = (v_{k1}, v_{k2}, \ldots, v_{kn})$ which are calculated at iterations on the basis of the global best position g=

(g_k, g_k, …, g_k) and its local best position $p_k = (p_{k1}, p_{k2}, \dots, p_{kn})$. In the m-th iteration the position and velocity of the k-th particle are calculated by:

$$v_k(m+1) = wv_k(m) + c_1r_1[p_k(m) - x_k(m)] + c_2r_2[g(m) - x_k(m)] \quad (7)$$

$$\begin{cases} v_k = v_{max} & \text{if} \quad v_k > v_{max} \\ v_k = -v_{max} & \text{if} \quad v_k < -v_{max} \end{cases} \quad (8)$$

$$w = w_{max} - \frac{w_{max} - w_{min}}{L} \quad (9)$$

$$x_k(m+1) = x_k(m) + v_k(m+1) \quad (10)$$

Where,

c_1, c_2 = acceleration coefficients
v_{max} = the maximum velocity
r_1, r_2 = random numbers ranging between 0 and 1

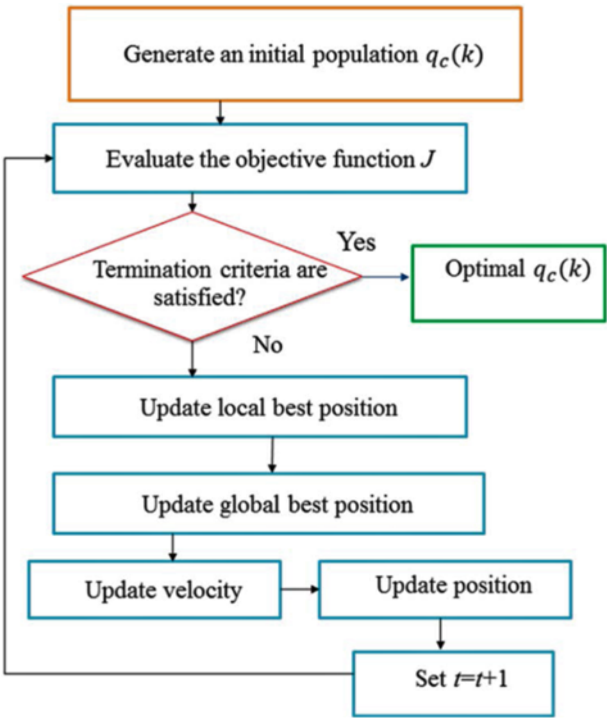

Fig. 3. Flowchart of PSO Optimization

w = the inertia weight
L = the maximum iteration number
w_{min} = the minimum inertia weight value
w_{max} = the maximum inertia weight value

The optimization procedure for the proposed objective function J can be detailed as follows (refer to Fig. 3):

1. Randomly initialize the swarm via assigning the local best position p_i, position x_i, and velocity v_i to every particle and the global best position g.
2. Assess the objective function for every particle.
3. Compare every particle's objective function value with its local best value p_{best}. If the value is better than the p_{best}, then update the value as p_{best} and x_k as p_k.
4. Find the particle yielding the best fitness value. The current best population evaluation is defined as g_{best} and its position as g.
5. Update every particle's velocity using Eqs. (7), (8), and (9).
6. Update every particle's position using Eq. (10).
7. Repeat Steps 2 – 6 until a desired fitness value is achieved or the maximum iteration number is met.

2.4 Micro-simulation

A bottleneck section including 5 on-ramps and 4 off-ramps on State Highway 1 (refer to Fig. 4) was selected as the test bed and simulated using AIMSUN. Analysis results of three-month data showed that the maximum traffic volume of the test bed was between 2,000 and 2,400 veh/h/ln, while its critical occupancy was located in the range 14 – 20%. Note that speed data is not available in the dataset provided by NZTA (NZ Transport Agency).

GEH statistic (Dowling *et al*., 2004) is employed to calibrate and validate the model based on the field data. The calibration and validation results showed that the model is acceptable for further analysis. AIMSUN gives modelers the freedom to build their own extensions onto the AIMSUN framework via application programing interface (API). Thus, an API was developed to apply the proposed method in AIMSUN.

3. Analysis Results

In this Section, the PSO method is verified against a well-

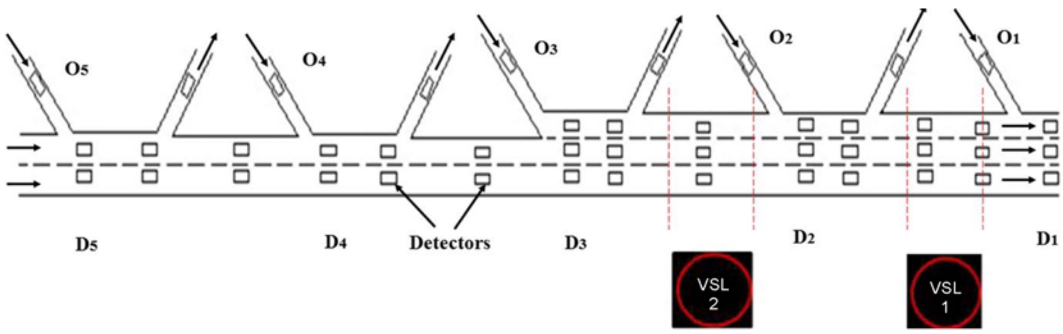

Fig. 4. Layout of the Study Area

Table 1. MOEs for the Tested Cases

MOEs	No control	Logic tree		PSO	
		Value	% change*	Value	% change*
TTT (veh-h)	1,719	1,622	-5.6	1,496	-13.0
Stop time/veh. (sec/km)	30	14	-49.8	4	-85.3
# of stops/veh	0.7	0.4	-40.9	0.2	-74.7
CO_2 (gm/km)	1.37×10^6	1.35×10^6	-1.46	1.32×10^6	-3.8
NOx (gm/km)	3,060	3,010	-1.6	2,918	-4.6

*Compared to no-control option

Table 2. F-test and T-test Results

		No control	Logic tree	PSO
		F-test p-value		
No control	T-test p-value		0.252	0.007
Logic tree		0.191		0.095
PSO		0.016	0.093	

Significance level: 0.05

known logic tree method (Allaby *et al.*, 2007). The no control case that represents a case without VSL controller is used as a benchmark. Table 1 presents MOEs (measure of effectiveness) computed for the test bed under different scenarios. The total travel time (TTT) computed using the logic tree based algorithm was reduced to 1,622 veh*h which resulted in 5.6% improvement compared to the no-control case. The same algorithm recorded around 50% improvement in average stop time duration per vehicle and 40% improvement in average number of stops per vehicle compared against the no control scenario. The PSO-based VSL algorithm outperformed all other tested cases, yielding the lowest TTT (improved by 13%). Significant improvements in emissions were observed because of the application of VSL.

T-test and F-test were performed to reveal the differences among the total travel time values computed using the tested cases, as shown in Table 2. For the logic tree VSL, the improvement was not that significant compared against the no control case. For the proposed algorithm, the improvement in TTT was statistically significant compared to the no control case.

Figure 5 shows TTT for the tested cases. It can be observed that the network without control yielded large variations in TTT. The variations in TTT were decreased due to the implementation of VSL. The network equipped with PSO based VSL resulted in the minimum variations among all the tested cases.

Figure 6 shows changes in average delay under different control scenarios. It can be observed that VSL was efficient in decreasing on-ramp delay. Meanwhile, a slight increase in mainline delay was recorded. Nevertheless, such increase can be compensated by delay time reductions at on-ramps.

Figure 7 shows traffic flow contour plots for different control cases. The figure showed that both VSL control cases yielded higher traffic volume near the detector D1 and D2 when compared with the no-control scenario. Fig. 8 shows speed contour plots

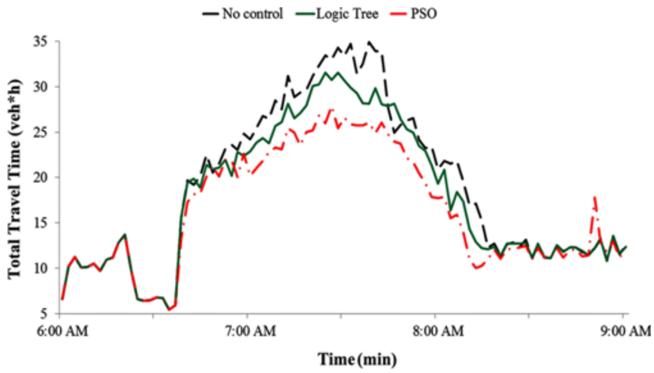

Fig. 5. Total Travel Time

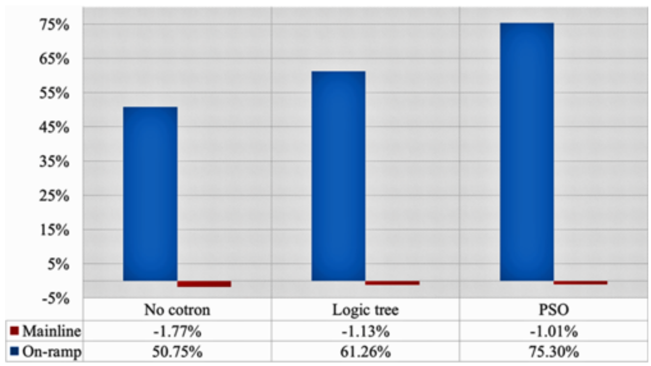

Fig. 6. Improvement of Average Delay in VSLs Control Scenarios

for the tested cases. Large variations in speeds were witnessed when no VSL was applied. These variations were decreased for both VSL cases. PSO based VSL case recorded the minimum variations in speeds.

4. Conclusions

This paper presents a PSO based VSL method to minimize flow breakdown probability at bottleneck sections and ensure a maximum utilization of current motorway infrastructure. The main findings of this research are:

1. The motorway section with the PSO based VSL outperformed the one with the logic tree based VSL. The mobility gains due to the proposed algorithm is significant compared to the no control scenario.
2. VSL has proven to be a valuable and efficient control tool to improve mobility and environmental performance of motor-

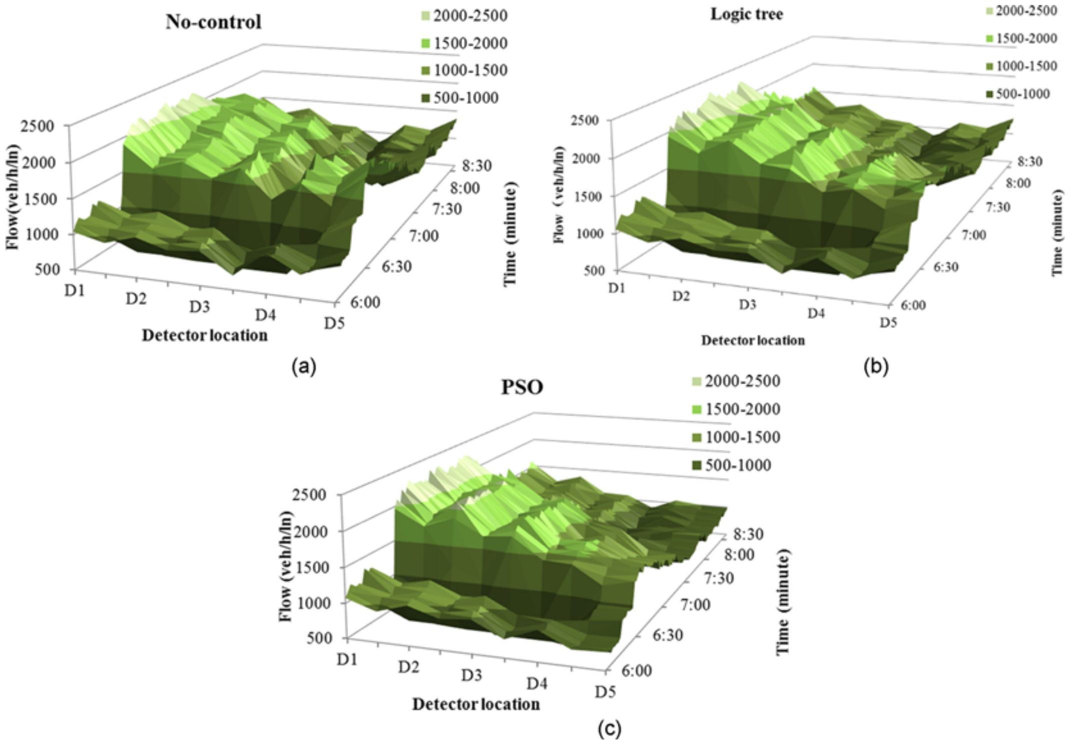

Fig. 7. Volume Contour Plots for Tested Cases: (a) No-Control, (b) Logic Tree, (c) PSO

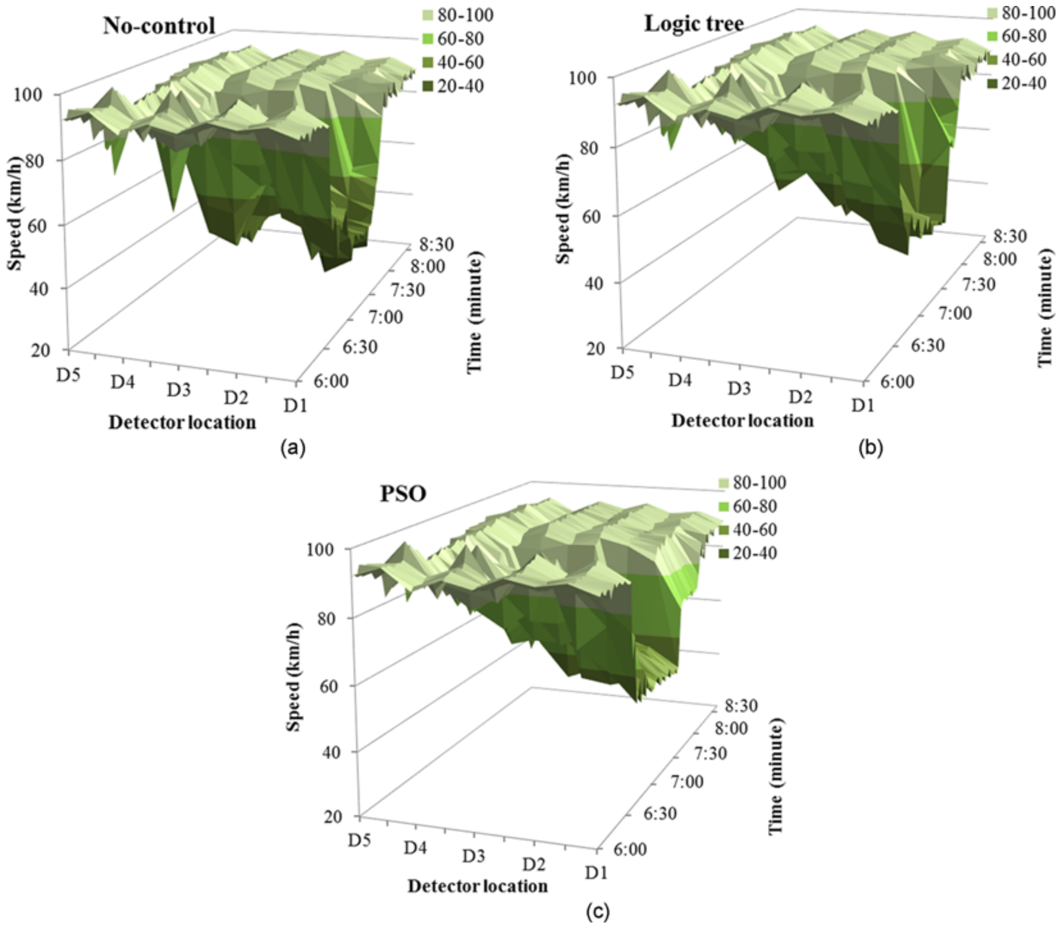

Fig. 8. Speed Contour Plots for Tested Cases: (a) No-Control, (b) Logic Tree, (c) PSO

way systems.

3. Although the application of VSL may cause a slight increase in mainline delay, such increase can be sufficiently compensated by delay time savings at on-ramps.

As discussed in Section 2, there remains a considerable discrepancy about the relationship between safety and mobility for VSL controlled segments. Some studies reported that safety benefits were achived at cost of increase in TTT; while other studies observed improvements in both mobility and safety after application of VSL. Thus, future works include assessing safety and mobility benefits caused by VSL and developing a robust VSL system to improve mobility under acceptable safety standards.

Acknowledgements

This study was sponsored by China Postdoctoral Science Foundation funded project (Project No. 2017M620434), the Alexander von Humboldt Foundation, Shaanxi Province Postdoctoral Science Foundation funded project (Project No. 2017BSHEDZZ38), Natural Science Basic Research Plan in Shaanxi Province of China (Project No. 2017JQ5033), the Fundamental Research Funds for the Central Universities (Project No. 300102218309, 300102218401, No. 300102218404).

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